The perceived quality of the urban residential environment

Poll, Henricus Franciscus Peter Maria van

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Chapter 3
Empirical research methods

3.1 Introduction

In the previous chapter it was concluded that the 'perceived quality of the urban residential environmental' may best be interpreted as a hierarchical multi-attribute concept. This approach was visualized in the model of environmental quality given in Figure 2.1 (Chapter 2). Quantifying perceived environmental quality is a complex problem because in quality assessment of residential environments many different features have to be considered simultaneously.

Behavioural decision theory (see, e.g., Keeney and Raiffa, 1976, Hogarth, 1987; Von Winterfeldt and Edwards, 1986) provides theories, models and methods for the analysis of multi-attribute objects[1]. This will be referred to as a multi-attribute evaluation.

In the remainder of this chapter the general research methodology is explained. A multi-attribute evaluation procedure involves several steps. The different steps are explained and for each step different methods and techniques are discussed (section 3.2). In section 3.3 three distinct research approaches that were used in the four empirical studies are presented. They have been developed on the basis of the different methods and techniques discussed in section 3.2. In section 3.4 these three approaches are compared. Their strengths and weaknesses are discussed. The chapter ends with some concluding remarks about the research methodology (section 3.5).

3.2 The general research methodology: the multi-attribute evaluation procedure

The quintessence of a multi-attribute evaluation procedure is that objects are thought to possess a 'value' or 'utility' for various reasons. Therefore, a complex object is seen as being composed of smaller constituting components, called attributes. Attributes are the relevant features or characteristics of the concepts or objects under consideration on which objects or concepts may have varying values. Objects, then, are evaluated on the underlying attributes. That is, objects are located on a scale for each attribute. Subsequently the weight of each attribute is determined. Weights express the relative importance of an attribute with respect to the overall value of an object. Attribute weight and evaluation of the object on the attribute are combined to yield a single-attribute value. Next, the single-attribute values are aggregated across the various attributes. This leads to an overall value of the object under consideration. On the basis of the overall value or utility of the objects (two or more), a decision (choice, preference) may be stated. Finally, sensitivity analysis may be performed to assess the robustness of the results, i.e., to assess the extent to which alterations in scale values, attribute weights, or aggregation rules may lead to different decisions. The term value is used when some kind of objective unit is available to quantify the score of the object on the relevant attributes. Utility is used to express the subjective value of the object on the relevant attributes.

More specifically, the quality of the urban residential environment is conceived of as possessing a subjective value. This value is determined by the value of the 'urban

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[1] The term 'objects' may be replaced by 'choice options', 'consequences', or 'concepts'. For the benefit of the general methodological discussion the term 'object' is used here. Furthermore it is used to indicate 'dwellings' and 'neighbourhoods'. The term 'concept' is used in relation to 'environmental quality'.

residential environment' on its underlying attributes, e.g., one's satisfaction with the dwelling, the neighbourhood, and the neighbours (see Figure 2.1, Chapter 2). The overall subjective value of the urban residential environment, then, is a weighted aggregation of its evaluations on the relevant attributes. So, for the assessment of the 'subjective value' (i.e., environmental quality) of 'multi-attribute objects' (i.e., urban residential environments), the following information is needed: what are the objects? What are the value-relevant attributes? What are the scores (evaluation) of the object on the relevant attributes? What is the relative importance (weight) of these attributes? What is the proper aggregation rule? Finally, how robust are the evaluation results (sensitivity analysis)? More formally, after identifying the object, several steps may be undertaken for the analysis of a multi-attribute object:

1. identify value-relevant attributes	2. evaluate objects on attributes	3. assign relative weights	4. aggregate weights and object scores	5. perform sensitivity analysis

In the following sub-sections solutions for answering the above questions are discussed in more detail. For each successive step several methods and techniques are discussed. In section 3.3 the specific research approaches used in the empirical studies are presented. This is done according to the topics raised in the questions above and discussed below.

3.2.1 Defining the objects

The central topic in this monograph is the concept of 'environmental quality' with emphasis on the quality of urban residential environments as explained in the previous chapter. These are the objects for the multi-attribute evaluation. The main goal of the latter is to assess the respondents' value-relevant attributes that affect the perceived quality of the urban residential environment and to assess their relative importance. In qualitative terms, the perceived quality of the urban residential environment is determined by a respondent's satisfaction with the dwelling, the neighbourhood, and the neighbours. In turn, satisfaction with the dwelling and the neighbourhood is determined by satisfaction with their lower-level attributes: the dwelling and neighbourhood attributes. Several sources could be identified that affect satisfaction with the various dwelling and neighbourhood attributes. These sources are the end-level attributes (see below). The evaluation should reveal the relevant attributes for assessing the quality of the urban residential environment and their relative importance.

3.2.2 Identification and structuring of value relevant attributes

The first step in a multi-attribute evaluation procedure is to identify and, if necessary, to structure value-relevant attributes.

identify value-relevant attributes	evaluate objects on attributes	assign relative weights	aggregate weights and object scores	perform sensitivity analysis

Several sources and methods may be used to identify and structure relevant attributes of objects. Relevant attributes can be elicited, for instance, by using common sense, by reviewing relevant literature, or by interviewing relevant people (e.g., experts, residents). Techniques available for interviewing are, for instance, direct questioning and indirect questioning (Alpert, 1971). In direct questioning the respondent is asked to motivate his preference for a given object. It is assumed that the respondent knows and will tell which attribute(s) determine his preference. Indirect questioning is any method in which a respondent is not asked directly which attributes influence his preference. An example is 'third-person' projective questioning. In this method the respondent is asked to indicate the importance of various attributes in determining most people's preference for a given object. Applying these techniques and methods may result in a set of attributes that are defined at various levels of concreteness. If this is so, the attributes may be structured in a hierarchical order.

Two approaches to structure attributes can be distinguished: an analytic or top-down approach and a synthetic or bottom-up approach. The 'top-down' approach starts with an inventory of abstract, semi-specified value-relevant attributes. These attributes are split up into more specific attributes (e.g., environmental quality into satisfaction with the dwelling, the neighbourhood, and the neighbours). The specification of attributes is continued until the attributes reach a level of concreteness on which the objects can be validly measured. These are the so-called 'end-level' attributes. The proposed model of 'urban residential quality', in the remainder referred to as the model of 'environmental quality' (see Chapter 2, Figure 2.1) was constructed according to this approach. The bottom-up approach involves a synthesis of well-specified, concrete attributes. Specific attributes are put together in groups so as to yield fewer and less well-specified general attributes. In turn, these so-called higher-level attributes are grouped together. This may continue until only one attribute remains, the 'top-level' attribute (Westenberg, 1993).

In both the 'top-down' and the 'bottom-up' approach abstract attributes are located higher up in the hierarchy of attributes than well-specified attributes. The abstract 'top-level' attribute branches into more and more specific attributes ending with the 'end-level' attributes. Altogether the attribute hierarchy is called a 'value tree'. Normally, the value tree is reshaped and pruned until all important attributes are in place. Redundancy of attributes should be avoided. Attributes may be called redundant if they have the same meaning or are correlated (Von Winterfeldt and Edwards, 1986). As a rule of thumb a value-tree contains eight to fifteen 'end-level' attributes with ten 'end-level attributes' as an optimum (Von Winterfeldt and Edwards, 1986; Westenberg, 1993). Usually, the 'top-down' approach results in a value-tree with small numbers of attributes per level but with many levels (deep hierarchical structure), whereas the 'bottom-up' approach usually results in flat, broad-based value-trees (Westenberg, 1993).

For the benefit of study 1 (see Chapter 4) a review of the literature was carried out to arrive at a set of residential attributes. In study 2 and 3 (see Chapters 5 and 6) attributes are inventoried by direct questioning. To structure the value-relevant attributes of 'environmental quality' both approaches discussed above are applied in the empirical studies. In study 1 the 'top-down' approach is used. In study 2 and 3 the 'bottom-up' approach is used.

3.2.3 Evaluation of objects

So far the value-relevant attributes have been identified and, if necessary, structured. The next step is to evaluate the objects on the underlying attributes.

identify value-relevant attributes	evaluate objects on attributes	assign relative weights	aggregate weights and object scores	perform sensitivity analysis

Several numerical estimation methods for evaluating objects are available (Von Winterfeldt and Edwards, 1986). Numerical estimation methods are, for example, direct rating, category estimation, ranking and ratio estimation. In 'direct rating' objects are located directly on a scale. For example, bicycles may be located directly on a monetary scale with respect to the attribute 'cost'. If no objective scale is available objects may be located directly on a subjective scale ranging from, e.g., 1 to 100. In 'category estimation', categories are formed first. The continuous 'cost' scale introduced above may be narrowed down to, for instance, five categories. These five categories may represent increasing price classes for bicycles. The discrete cost score of the various bicycles may now range from 1 to 5. In case of a subjective price scale (inexpensive-expensive) several levels in between may be used (categories). The levels are called 'equi-distant', that is, the difference between, for instance, level 1 and level 2 is supposed to be the same as the difference between level 4 and level 5. In the 'ranking method' objects are rank-ordered according to their attractiveness or preference. The most attractive or preferred object is given the highest ranking. The 'ratio estimation method' for value measurement is similar to the one for 'weight estimation', it will be discussed below.

To evaluate objects, different evaluation methods may be used. Objects may be evaluated either 'decomposedly' or 'holistically'. In the first case, the object is separately evaluated on each relevant attribute. In the second case, objects are evaluated as a whole, according to their attractiveness or preference. For both types of evaluations the estimation methods described above may be used.

In the study 1 (Chapter 4) objects are evaluated both decomposedly and holistically using category estimation, in study 4 (Chapter 7) objects are judged holistically, by ranking them according to attractiveness. In studies 2 and 3 (Chapters 5 and 6) objects are not evaluated (see section 3.3.2).

3.2.4 Assignment of relative weights

The next step in the multi-attribute evaluation procedure is the assessment of relative attribute weights.

identify value-relevant attributes	evaluate objects on attributes	assign relative weights	aggregate weights and object scores	perform sensitivity analysis

Weights are used to express the importance of an attribute with respect to the objects that are valued. Suppose the relationship between the value of an object on an attribute and the overall value of the object is linear. If the attribute value increases with one unit, the attribute weight gives the extent of the resulting increase in the overall value of the object. Mostly, attribute weights are not absolute values but are somehow estimated in relationship to each other, therefore they are called relative weights.

Several methods for attribute weight elicitation are available. Among them are multiple regression analysis, ranking and ratio weighting, conjoint analysis (also known as judgement analysis or policy capturing), pair-wise comparison, swing-weighting, the trade-off method, pricing out, and lotteries (see, e.g., Clemen, 1991; Hair Jr, Anderson, Tatham and Black, 1992; Von Winterfeldt and Edwards, 1986; Westenberg, 1993). Some of these methods will be elaborated below.

One property of multiple regression analysis is that so-called 'regression weights (B) are estimated. The value of a 'regression weight' indicates the extent to which the dependent variable (i.e., a higher-level attribute) changes if the independent variable (i.e., a lower-level attribute) changes with one unit. In case of two or more lower-level attributes, as in a multiple regression analysis, these weights are standardized because variables may be expressed on different scales. The 'standardized regression coefficients' or 'beta-coefficients' (β's) of the lower-level attributes are comparable since they are expressed on a common scale. In this way a 'β-coefficient' may be used to indicate the relative importance of a lower-level attribute. Multiple regression analysis is one of the research methods used to elicit the relative importance of environmental quality attributes (study 1, see Chapter 4). Therefore it will be discussed in more detail below (see section 3.3.1).

Another weight estimation procedure is the ranking and rating of attributes with respect to their relative importance for the evaluation of the object. 'Ranking and rating' is a weighting method frequently used in a Multi-Attribute Utility Analysis (MAUA). First, attributes are rank-ordered from most important to least important. Subsequently, attributes are rated on an interval or ratio scale. In interval scaling the most important attribute is assigned a value of, for instance, 100. This attribute serves as anchor point. All other attributes are assigned values equal to or lower than the anchor point. The difference in importance among attributes is given by the differences among the assigned values. In ratio scaling the least important attribute is used as an anchor point and assigned a value of, for instance, 10. Another attribute considered to be three times as important as the anchor attribute then receives a rating of 30. In this case the difference in importance is given by the ratio between any attribute and the least important attribute. Usually, the obtained rankings and ratings are standardized in order to make comparisons between respondents possible. Rules for standardizing and transforming rankings into scores on an interval scale can be found in Von Winterfeldt and Edwards (1986), rules for standardizing ratings can be found in Voogd (1983). MAUA is a second method used to analyze the concept of environmental quality (study 2 and 3, see Chapters 5 and 6). It will be explicated below (see section 3.3.2).

Conjoint analysis may be used, among other purposes, for the estimation of the relative importance of value-relevant attributes. In a standard 'conjoint analysis' experiment respondents are presented with a number of representations of objects (e.g., representations of neighbourhoods), so-called profiles. The profiles are experimentally designed on the basis of predetermined attributes and attribute levels. Respondents are presented with the profiles and are asked to judge them holistically, for instance, by ranking them according to their attractiveness. From the rankings, provided by the respondent, and the specified attribute levels, predetermined by the researcher, the relative importance of the attributes is reconstructed. Conjoint analysis is a third research method employed in the analysis of the concept of environmental quality (study 3, see Chapter 7). It will be discussed in more detail below (see section 3.3.3).

Other weight elicitation techniques are pair-wise comparison, swing-weighting, and the trade-off method. In the pair-wise comparison method, a respondent is presented with all possible pairs of attributes. For each pair the respondent indicates which attribute is more important. After repeated comparisons or after comparison of each pair by many different respondents, a 'frequency' value may be obtained that indicates how many times attribute 'x' is preferred over attribute 'y'. A scaling technique may be used to identify the location of a specific attribute on an importance scale on the basis of its 'frequency' value. A higher score on the scale indicates a higher importance of a specific attribute. (For a discussion of scaling techniques see, for instance, Meerling, 1981). An extension of the aforementioned method is the trade-off method. In the 'trade-off method' two objects are considered simultaneously both differing on only two attributes. The first object is better on one attribute and worse on the other, in the second object it is the other way around. The respondent indicates which object is preferred and by doing so he or she also indicates the more important attribute, that is, the attribute whose outcome is best on the preferred object. Subsequently, the more important attribute is described on a less desirable level in the preferred object. An alternative is the improvement of the more important attribute in the non-chosen object. This is continued until the respondent has no distinct preference for either object. The respondent is considered to be indifferent between the two objects. The extent of the change is a measure for the relative importance of the attribute. This method takes into account that a loss in the value of one attribute may be compensated by a quantified increase in another attribute (Borcherding, Schmeer and Weber, 1993). In swing-weighting the respondent starts with an alternative that is worst on all attributes. The respondent is then asked to change one attribute at a time from the worst to the best possible value. The respondent starts with the attribute whose 'swing' from low to high would yield the largest improvement of the alternative, then the second best attribute and so on. In this way an importance ranking of attributes is achieved. Furthermore, the value of the improvement by the 'swing' of the most important attribute from the worst to the best possible value is, arbitrarily, set at 100. The extent of improvement of the alternative by the other attributes' swings is expressed as a percentage of the swing on the 'best' attribute. These percentages are standardized to obtain the final attribute weights (Clemen, 1991).

Compared to the 'ranking and rating method' above, the latter three weight estimation methods are more laborious to perform. Furthermore, the 'ranking and rating method' is usually employed in attribute weight assessment of hierarchically structured concepts, because this method is easier to apply to nested attributes. Such is the case in the present evaluation of the concept of environmental quality. The use of the 'trade-off method' and 'swing-weighting' is usually confined to non-hierarchically structured (flat) multi-attribute concepts (Borcherding et al., 1993).

3.2.5 Aggregation

Once the values of an object on the relevant attributes and the attribute weights have been obtained they may be combined to yield an overall value for the object. This is done using an aggregation rule.

identify value-relevant attributes	evaluate objects on attributes	assign relative weights	aggregate weights and object scores	perform sensitivity analysis

The aggregation rule reflects the relationship between the overall evaluation of the object on the one hand and the attribute information about the object (scores on attributes, weights) on the other hand.[2]

To aggregate, first each attribute value of the object and its weight are combined. This results in a so-called 'single-attribute subjective value'. Usually, the attribute value of the object and attribute weight are multiplied to yield the 'single-attribute subjective value'. Next, these single-attribute values are combined, which results in an overall value for the object. Frequently, an 'additive model' is assumed. The model is also known as a 'main effects model'. This means that respondents are assumed to just add up the 'single-attribute subjective values' to arrive at an overall value for the object at hand. An extension of the additive model is a composition rule using 'interaction terms'. It is similar to the 'additive' model in that it also assumes that respondents simply add up the 'single-attribute subjective values'. In addition, however, it allows for combinations of two or more levels of certain attributes to be of more or less value than simply their sum. Adding interaction terms might improve the model's predictive power (the 'model fit'). However, the benefits of adding interaction terms to the model may not weigh up against the disadvantages of a more complicated design that is necessary to study interaction terms. Main effects usually account for the biggest part, about 80%, of the proportion of explained variance in the observations, while two-way interaction terms typically add only about three to six percent, and three-way interaction terms add only another one percent to the proportion of explained variance in the data (Louviere, 1988).

There are alternative, that is non-additive, model types for aggregation such as the distributive model, the dual-distributive model, or the multiplicative model (Louviere, 1988; Von Winterfeldt and Edwards, 1986). But the 'additive' model is the most simple one. It also is the most commonly used model in a multi-attribute evaluation procedure (Leung, 1978; Louviere, 1988; Von Winterfeldt and Edwards, 1986). The choice for an additive model is a trade-off between a reliable (robust, see below) model form and a best practical means of representing the structure of respondents' preferences.

3.2.6 Sensitivity analysis

Finally, after the overall values of the objects have been assessed, sensitivity analysis may be performed.

identify value-relevant attributes	evaluate objects on attributes	assign relative weights	aggregate weights and object scores	perform sensitivity analysis

Sensitivity analysis is a check on the stability or robustness of the model outcomes. It refers to the extent to which changes in the model parameters (relative weights) or model form (the aggregation rule) lead to different overall 'subjective values' of the objects, hence may lead to different decisions (Leung, 1978; Van Den Brink, 1993). For instance, once an aggregation rule has been drawn up the relative importance of the attributes may be changed. Attributes may be treated as equally important (equal weighting), or the rankings of the relative weights instead of their numerical values may

[2] It should be noted that in this kind of modelling, i.e., 'structural modelling', the aggregation rule only represents the presumed structure of preference. It is the result of an input-output analysis. What actually goes on inside a respondent's mind is not necessarily captured by structural modelling. In contrast, 'process tracing' (see, e.g., Van Dam, 1993) aims at understanding what is going on inside a respondent's mind.

be used. Yet another possibility is to set the relative weight of some attributes at zero. This is the case if, for instance, only the three most important attributes of a given set are considered in estimating the overall subjective value. Sensitivity to model form may be analyzed by employing different aggregation rules (see section 3.2.5). The extent of the changes in the overall 'subjective value' of the object may determine the robustness of the model.

Sensitivity analysis is only useful in cases were actual decisions (choices, preferences) on two or more objects have to be made. In this monograph the multi-attribute evaluation procedure is used to analyze a respondents preference structure, that is, to analyze what attributes are considered important and how important they are in relation to each other. Therefore, making actual decisions and therefore performing sensitivity analysis is beyond the scope of this monograph.

3.2.7 Summary and discussion of general methodology

In the previous sections the steps of a multi-attribute evaluation procedure have been discussed at length. For each of the steps several methods and techniques have been introduced and discussed. They are summarized in Table 3.1. Now some important methodological issues can be discussed.

Table 3.1 Overview of the previously discussed methods and techniques for the subsequent steps in a decision analysis procedure.

attributes	object evaluation	weight assignment	aggregation	sensitivity analysis
inventory: -how: -common sense -literature -key persons -who: -respondent -researcher techniques: -questioning (direct or indirect) structuring: -'top-down' -'bottom-up'	estimation method: -direct rating -category estimation -ranking + rating evaluation type: -decomposed -holistic	methods: -multiple regression analysis -ranking + rating -Conjoint Analysis -pair-wise comparison -swing-weights -trade-off	rule type: -additive -linear -multi-linear -non-additive	-model parameters -model form

Firstly, different methods to identify and structure relevant attributes have been discussed (see Table 3.1, leftmost panel). The inventory of attributes may be done by the researcher by reviewing relevant literature or by using common sense. The results of this method have been presented in Chapter 2. Also, attributes may be elicited from respondents by questioning them. The results of the latter method then could be used as a check on the results obtained by the researcher. Furthermore, two methods to structure attributes have been discussed: the 'top-down' approach and the 'bottom-up' approach. The 'top-down' approach has been used by the researcher to structure the attributes that came up from the review of the literature and resulted in the value-tree given in Figure 2.1: the proposed model of environmental quality or theoretical model (see Chapter 2). The 'bottom-up' approach is employed as well. In one of the empirical studies (see below) this is done by residents. The resulting value tree will be designated as the empirical model of environmental quality (see Chapter 5). It will be interesting to observe to what extent the contents and structure of both models converge.

The second issue concerns the type of modelling. This is especially important for the way in which the attribute weights are assessed. Two types of modelling may be distinguished: constructive modelling and reconstructive modelling. Typically, in 'constructive' modelling a multi-attribute concept or object is built up from its underlying attributes. Objects are scored separately on each of the value-relevant attributes. The relative importance of the underlying attributes is estimated either directly or indirectly. An example of a direct weighting method is the 'ranking and rating' method. The 'trade-off' method and 'pair-wise comparison' are examples of indirect weighting methods. By combining objects' scores and relative weights into single-attribute subjective values and subsequent aggregation of these values, the overall value of the object is obtained. A MAU-analysis is a typical constructive modelling approach. On the other hand, in 'reconstructive' modelling, the overall preference, by ranking or rating, for an object is broken down to yield the relative importance of the underlying attributes. Both 'multiple regression analysis' and 'conjoint analysis' are examples of reconstructive modelling.[3]

Finally, in constructive modelling, i.e., a MAU-analysis, the relative attribute weights are usually assessed irrespective of the objects under consideration. This is in contrast to reconstructive modelling in which relative attribute weights are derived from the observed covariance between overall scores of one or more objects and the objects' scores on the underlying attributes. In a typical Conjoint Analysis experiment respondents judge more than one object. Relative weights then can be assessed on an individual level. In a multiple regression analysis respondents usually provide judgements on one object. Relative weights result from an analysis on group-level data. It will be interesting to assess the extent of correspondence between the results of the 'constructive' and 'reconstructive' modelling approaches, especially with respect to the assessment of the relative importance of the residential attributes.

Thus, as already announced in Chapter 2 the following methodological research questions will be addressed:

- What is the extent of convergence between the results of the 'top-down' and 'bottom-up' ways of structuring attributes?
- To what extent will different types of modelling the respondents' preference structure for the perceived environmental quality (constructive versus reconstructive) lead to the same results?

3.3 Introduction to three research approaches

Two main research questions that are addressed in this monograph with respect to residential attributes affecting environmental quality are:

- what are the value-relevant residential attributes?
- what is the relative importance of the value-relevant attributes?

Together with the methodological issues discussed above this has led to the design of three research approaches. In this section the approaches are discussed at greater

[3] 'Constructive' modelling is also known as 'compositional' modelling, the term 'build up' approach may be noted as well. 'Reconstructive' modelling is also known as 'decompositional' modelling. It is also referred to as 'break down' approach.

length.

For the analysis of the concept of 'environmental quality' four empirical studies were designed and carried out. The studies were designed on the basis of three types of analyses already briefly introduced in the 'weight assignment'-section (section 3.2.4). These are: Multiple Regression analysis, Multi-Attribute Utility analysis, and Conjoint analysis. The main difference between the three approaches is the way in which the relative importance of residential attributes is assessed (see above). Other differences concern: the way in which attributes are collected and by whom, the type of evaluation made (decomposed versus holistic), the type of object (real or experimental objects) and the level of weight assessment (individual level versus group level). These issues are discussed in the sections below. 'Aggregation' of single-attribute subjective values (section 3.2.5) and 'sensitivity analysis' (section 3.2.6) will not be addressed in the remainder of this chapter. This is so because, as already pointed out, to aggregate usually an additive model form is assumed. It was concluded that this was the best practical means for representing the structure of a respondent's preference. The additive model form is adopted for each of the three approaches. As already explained above, the focus of this monograph is on analyzing respondents' judgements rather than on making decisions. Therefore sensitivity analysis will not be performed.

Below, the 'Hierarchical Multiple Regression (HMR)' approach (section 3.3.1) is discussed. Next the 'Multi-Attribute Utility (MAU)' approach (section 3.3.2) is discussed and, finally, 'Conjoint Analysis (CA)' (section 3.3.3). All three approaches are discussed in terms of the steps of the general methodology outlined in section 3.2. Summarized, these steps were as follows:

1. Identification and structuring of attributes.
2. Evaluation of objects on each attribute.
3. Assessment of attribute weights.

3.3.1 Hierarchical Multiple Regression (HMR) approach

In the first empirical study (study 1, Chapter 4) on the concept of 'environment quality' the Hierarchical Multiple Regression approach (HMR), a reconstructive modelling type, is used. Multiple regression analysis is the main analyzing technique (see, e.g., Hair Jr. et al., 1992; Hays, 1988; Van Knippenberg and Siero, 1991). Multiple regression analysis is a statistical technique to analyze the relationship between a single criterion or dependent variable (i.e., higher-level attribute) and two or more predictor or independent variables (i.e., lower-level attributes). Multiple regression analysis may be used for prediction. Normally it is used to assess the extent to which the observed variance in the dependent variable is explained by the observed variance in the independent variables, also referred to as the 'model fit'. It is also used to assess so-called 'standardized regression weights' (β's). In the present study, this is a very important property, since the 'β-coefficient' may be used to indicate the relative importance of a lower-level attribute (Meerling, 1981). These specific properties of multiple regression analysis, estimation of the 'regression weights' and assessing the 'model fit' are used for the analysis of the concept of environmental quality.

The specific steps of the 'HMR' approach undertaken in the first study (see Chapter 4) are discussed below.

Step 1. Identification and structuring of attributes. In a 'HMR' approach, attribute selection and structuring of the attributes is usually done by the researcher. Methods that may be used to select and structure attributes were discussed in section 3.2.1. For the first study, a survey of the literature on environmental quality was conducted to identify value-relevant attributes. Next, the so-called 'top-down' approach was employed to structure these attributes. This resulted in the theoretical model of 'environmental quality' given in Figure 2.1 (Chapter 2). It starts with the top-level attribute 'environmental quality' represented by 'residential satisfaction'. The top-level attribute branches out into more specific, lower-level attributes, in this case satisfaction with the dwelling, the neighbourhood, and the neighbours, respectively. In turn, some of these attributes branch out further into even lower-level attributes. This continues until the end-level attributes are reached, that is, attributes on which the object may be validly measured. The result is a value-tree for environmental quality. The attributes in the value-tree will serve as criteria for the evaluation of the 'residential environment'. The structure of the value-tree indicates what lower-level attributes are thought to affect the higher-level attributes, or, in statistical terms which are the independent variables and which is the dependent variable in the analysis.

Step 2. Evaluation of objects on each attribute. The object of interest is the 'residential environment'. In this study actual residential environments are evaluated on the attributes in the theoretical model given in Figure 2.1 (Chapter 2). Furthermore, this is done by residents living in a particular residential environment. They are asked to express the extent to which they are satisfied with or annoyed by their present residential situation on each attribute. It should be noted that in a 'hierarchical multiple regression analysis' respondents provide data on both the dependent and independent variables, that is, respondents evaluate their residential situation on all of the attributes in the model. In case of 'higher-level' attributes these evaluations can be designated as 'overall' or 'holistic' evaluations.

Step 3. Assessment of attribute weights. After the data are collected and entered into the computer several multiple regression analyses are performed. This is done because of the hierarchical nature of the theoretical model: each higher level attribute is regressed on its lower-level attributes. This implies that some of the attributes are the independent variables in one analysis and the dependent variable in an other. This is the case for the level-2 attributes: the dwelling and the neighbourhood and all the level-3 neighbourhood attributes (see Figure 2.1).

The analyses should reveal the relative importance of the residential attributes. For this purpose the 'standardized regression weights' are calculated. In the regression analysis the independent variables are weighted, that is, their relative contributions to the dependent variable are estimated. For each independent variable this is done by estimating the influence of the particular variable on the dependent variable while the influence of other independent variables is held constant. These numerical values are called 'regression weights' or 'coefficients'. After standardization into so called 'beta-coefficients', the relative importance of the predictor variables may be compared (Hays, 1988). In this way relative weights are assessed indirectly. Regression weights are calculated using the method of 'ordinary least squares (OLS)'; see below.

The 'beta-coefficients' obtained in a multiple regression analysis should be handled with care. First their validity depends on the extent of collinearity among the independent variables. Collinearity refers to the association between the independent variables. A high association between the independent variables makes determination of the contribution of each independent variable difficult because the effects of the independent variables are mixed. Second, the 'beta-coefficients' are only meaningful in the context of the other variables in a specific analysis. Adding a variable may affect the magnitude and/or the sign of the other variables. So, the relative importance of the variables can only be interpreted meaningfully within the context of the variables in the analysis. Finally the range of values for a given independent variable (lower-level attribute) affects the magnitude of its 'beta-coefficient'. The larger the range, the higher the 'beta-coefficient' (Hair Jr. et al., 1992).

In addition, the extent of the 'model fit', that is, the extent to which the independent variables accurately describe the dependent variable will be assessed. This is done by assuming an additive linear relationship between dependent and each independent variable. Scores on the variables were analyzed using the method of 'ordinary least squares (OLS)'. In this procedure the sum of the squared differences between the observed values of the dependent variable and the estimated values on the basis of the independent variables is minimized. The 'multiple correlation coefficient' (R^2) gives the proportion of the variance that could be explained by a linear combination of the independent variables, with the F-statistic serving as test criterion (Hair Jr. et al., 1992; Hays, 1988).

In summary: In study 1 (Chapter 4) the Hierarchical Multiple Regression (HMR) approach, a reconstructive modelling approach, is employed. In the 'HMR' approach residents evaluate their present residential situation on the attributes of the theoretical model of 'environmental quality'. This is done by means of a written questionnaire. Respondents provide overall evaluations as well as single-attribute evaluations. By means of several multiple regression analyses the relative weights of the residential attributes are estimated. Relative weights of the residential attributes are estimated on group-level data, since each respondent only evaluates one object: his or her own residential environment.

3.3.2 Multi-Attribute Utility (MAU) approach

The second approach that is discussed in more detail is a constructive modelling approach and originates from Multi-Attribute Utility Theory (MAUT;[4] see, e.g., Einhorn and McCoach, 1977; Hogarth, 1987; Von Winterfeldt and Edwards, 1986; Yilmaz, 1978). It is used in study 2 and study 3 (Chapters 5 and 6). MAUT has been developed within the field of behavioural decision theory. It encompasses a number of models and measurement procedures to analyze multi-attribute concepts. It is usually applied in decision making on well-defined decisions under certainty, that is, decisions in which the alternatives and the possible outcomes are known.

Most of the models and measurement techniques used in a MAU-analysis are rather formal, and although considered methodologically elegant they are difficult to apply in real-life decision making (Leung, 1978). For this reason simple methods have been developed such as the 'simple multi-attribute rating technique (SMART)' (see, e.g., Von Winterfeldt and Edwards, 1986) or the 'simple multi-attribute utility procedure (SMAUP)' (Einhorn and McCoach, 1977). In this monograph 'SMART' is adopted. Note, that, again, several appellations for quite similar techniques or procedures are used.

4 Various appellations can be found throughout the literature for the tools of value measurement: MAUT, MAUM, MAUA, and MAU. The T stands for theory, the M for models, and the A for analysis.

For the explanation of the method employed in the second and third study (see Chapter 5 and Chapter 6) only the identification and structuring of attributes and the assignment of relative weights is discussed in more detail.

Step 1. Identification and structuring of attributes. In contrast to the 'HMR' approach above, in which both identification and structuring of the attributes was done by the researcher, in the 'MAU' approach this is done by the respondents themselves. Furthermore, the 'bottom-up' approach instead of the 'top-down' approach is used for structuring the attributes. In a face-to-face interview, respondents are presented with a set of possibly relevant residential attributes. This set was obtained on the basis of the results of the first study (see Chapter 4) in which the 'HMR' approach was employed. Two separate lists are used: one containing dwelling attributes, the other neighbourhood attributes. For each set the following tasks are carried out by the respondent to identify value-relevant residential attributes and to assess their structural relationship:

- adding relevant attributes,
- importance selection of attributes,
- grouping of attributes according to similarity.

The tasks are carried out with reference to dwellings and neighbourhoods in general, as opposed to the 'HMR' approach in which respondents are specifically asked to evaluate their own residential situation.

Firstly, each respondent is asked to carefully read the list and add attributes which he or she thinks of as relevant but which are not mentioned in the list. These are added to the list. In this way a full array of relevant residential attributes for each respondent is obtained. Secondly, each respondent is asked to select important attributes from the list. This results in a set of important 'end-level' attributes.

Following the 'bottom-up' approach (see section 3.2.2), the 'end-level' attributes are grouped into higher-level attributes. For this purpose '(dis)similarity' among attributes serves as a grouping criterion. Each respondent is asked to group the attributes according to their similarity. Respondents are free to put as many attributes as necessary in one group. Also, they are free to make as many groups (i.e., higher-level attributes) as necessary. In this way, using the bottom-up approach, each respondent designs an individual value tree of residential attributes. The value trees provided by the respondents then are aggregated across respondents. The resulting overall value-tree is designated as the empirical model of environmental quality. The contents and structure of the empirical model is compared with the theoretical model in Figure 2.1.

Step 2. Evaluation of objects on each attribute. Because the respondents are asked to carry out the task with reference to residential environments in general, actual evaluations of residential environments are not requested.

Step 3. Assessment of attribute weights. This is done using the ranking and rating method (see section 3.2.3). First, higher-level attributes (groups, see above) per level are rank-ordered from most important to least important with respect to the quality of the residential environment. Subsequently attributes are rated on an interval scale (see section 3.2.3). Next the procedure is repeated for the attributes within one higher-level attribute (attributes per branch). Ratings for the higher-level and lower-level attributes are separately standardized. In a hierarchical structure relative weights for the end-level attributes are obtained by multiplying the relative weights of the attributes through the branches of the value tree. End-level weights then are obtained by multiplying weights for the lower-level attributes with the weight for its specific higher-level attribute. Due to the standardization, end-level attribute weights are expressed on a common scale, so individual end-level attribute weights may be compared.

In summary: In study 2 and study 3 (Chapters 5 and 6) the Multi-Attribute Utility (MAU) approach, a constructive modelling approach, is used. In the 'MAU' approach each respondent makes an inventory of 'value-relevant' residential attributes and structures these attributes according to the 'bottom-up' approach into a 'value tree'. The various individual value trees are joined into a so-called empirical model of environmental quality. For each respondent relative attribute weights are assessed. This is done directly using the 'ranking and rating' method. Weight assignment is carried out irrespective of the present residential situation of the respondent but with respect to the quality of dwellings and neighbourhoods in general.

3.3.3 Conjoint Analysis (CA) approach

The third, and final approach that is discussed is Conjoint analysis, a reconstructive modelling approach (for reviews see: Green and Srinivasan, 1978; Green and Srinivasan, 1990; Louviere, 1988; Vriens and Wittink, 1990). It will be used in the fourth empirical study (Chapter 7). Conjoint analysis is a multivariate technique used specifically to understand the structure of a respondent's preferences for objects, whether physical (products) or non-physical (services, ideas), real or hypothetical. It was developed in the mid 1960's. Nowadays it is applied in various research fields. In marketing research the technique is usually called 'conjoint analysis' or 'conjoint measurement', see, for instance, Okechuku (1994), Vriens (1992), and Vriens (1994). In the psychological sciences it is known as 'judgement analysis' or 'policy capturing', see, for instance Westenberg (1993). In the social sciences it is also known as 'factorial survey', see, for instance, John St and Bates (1990), Rossi and Anderson (1982), Thurman (1989), and Thurman (1986). As was noted before, again various appellations for the same technique may be encountered in the literature. In this monograph the term 'conjoint analysis' is adopted.

Green and Srinivasan (1990) have defined conjoint analysis as '. . . any decompositional method that estimates the structure of a consumer's preferences, given his or her overall evaluation of a set of alternatives (objects) that are prespecified in terms of levels of different attributes'. Typically, in a 'conjoint analysis' experiment respondents are presented with a number of representations or descriptions of objects, so-called profiles. The profiles are designed by combining predetermined attributes, relevant to the object, at various levels. The technique enables researchers to manipulate the profiles by using specific combinations of attributes and attribute levels. Respondents are then asked to provide an overall evaluation of the profiles. This can be done by, for instance, scale ratings or by ranking the profiles according to preference. These evaluations are used to estimate the relative weights of the attributes.

The procedure for the 'CA'-experiment conducted in study 4 (see Chapter 7) is explained below.

Step 1. Identification and structuring of attributes. In contrast to the 'MAU' approach discussed before, attribute selection is usually done by the researcher when designing the stimuli for a 'CA' experiment. This was also the case in the 'HMR' approach. Attributes and their hierarchical structure are derived from the results of study 2 (see Chapter 5).

Step 2. Evaluation of objects on each attribute. In a Conjoint Analysis experiment respondents provide overall (holistic) evaluations of the objects at hand: residential environments. The objects are not evaluated on each of the value-relevant attributes separately. This is in contrast to the 'HMR' approach and the 'MAU' approach (see above). Furthermore, in a 'CA' experiment respondents evaluate objects that vary systematically on the values of the underlying attributes. In an ideal experimental setting, respondents would evaluate a number of actual residential environments which vary systematically on the value-relevant residential attributes. However, residential environments which actually do so are hard to find! Therefore, the researcher may use experimentally designed representations or descriptions of objects, rather than actual neighbourhoods. Because of this the discussion of the 'CA' approach at this point needs to be done at greater length than the ones before. In the following subsections the steps for (1) the design and (2) the evaluation of experimental objects are explained in general. The design of the actual stimuli used in the experiment is explained in detail in Chapter 7. The steps are discussed below and can be summarized as follows (Hair Jr. et al., 1992; Vriens and Wittink, 1990):

1. Designing experimental objects (profiles):
   - 1a. attributes selection,
   - 1b. level specification,
   - 1c. creating stimulus design,
   - 1d. representation of stimuli,
   - 1e. number of attributes.
2. Data collection:
   - 2a. presentation method for stimuli,
   - 2b. preference measure.

Ad 1. Designing experimental objects: the profiles.

In designing stimuli for a 'CA' experiment several aspects must be taken into consideration: the attributes to be used, the level specification of the attributes, the actual design of the stimuli, and the representation of stimuli. Furthermore, if the number of value-relevant attributes is large, precautions are necessary to avoid practical difficulties (see below).

1a. Attribute selection. When selecting attributes, it is important that all attributes that affect the value of the objects, in this case dwellings and neighbourhoods, are included. Attributes should be included that best differentiate between dwellings or neighbourhoods. Therefore, the value tree should be checked on the presence of redundant attributes.

The number of attributes included is important as well. Respondents are asked to rank order stimuli with regard to attractiveness. These responses are used to assess the relative weight of the underlying attributes. The number of stimuli required for reliable assessment of attribute weights depends (among others, see below) on the number of attributes used to describe the objects. If the number of attributes becomes large either reliability will decrease (if the number of stimuli is held constant), or the number of stimuli that has to be judged increases. Increasing the number of stimuli may result in demanding and time-consuming tasks for the respondents. In the present 'CA'-experiment as many attributes as practically feasible are used. Attribute selection, as explained above, is done on the basis of the value tree obtained in the 'MAU'-analysis (Chapter 5).

1b. Level specification. After selecting the relevant set of attributes, levels must be specified. First it is important that the full range of possible values is captured and that the specified minimum and maximum value should be realistic. Take, for instance, the purchasing of a 'CD-player'. The price may be a relevant attribute. The range should reflect current market prices. So, price range may be set at Dfl 250.00 to Dfl 1300.00. On the other hand, it is conceivable that the range of values can not be quantified. In that case the range can be specified qualitatively, for instance, a price range could be set from inexpensive to expensive.

After the range has been established, the number of levels must be specified. The number of levels should be balanced across attributes. It has been demonstrated that with an increasing number of levels, the relative weight of an attribute increases as well (Hair Jr. et al., 1992). As was the case with the number of attributes, adding levels increases the number of necessary parameter estimations. On the other hand, the use of more than two levels allows for a check on the functional form of the subjective value function. In the present 'CA'-experiment attribute levels will be indicated qualitatively. For practical reasons each attribute is described at two levels, one level representing a favourable object score, the other representing an unfavourable score. A linear relationship between preference and level of the attribute is assumed.

1c. Creating stimulus design. Once the attributes and their levels have been determined and the functional relationship between attribute level and preference has been established, the stimuli can be constructed. Stimuli are a representation of the object on the basis of combinations of different attributes and attribute values. If the number of attributes and levels is small, respondents may be presented with all possible combinations. For instance if an object is defined by three attributes (n) on two levels each (m) the number of all possible stimuli is eight (m^n). A design in which all possible combinations of attributes and attribute levels are used is called a 'factorial design'. When the number of attributes and/or the number of levels increases the number of possible different profiles increases exponentially. By using, for instance, four attributes with each three levels the number of possible profiles is already eighty-one.

A 'factorial design' enables one to assess all possible interaction effects. Usually this is not necessary. As was indicated before, 'main effects' generally tend to account for 80% of the variance in the observations. Furthermore the presumed model form, the 'additive model' (see above), allows for the estimation of only 'main effects'. For the estimation of 'main effects' only, a so-called 'fractional factorial design' may be used. For instance, a set of neighbourhood profiles may be designed on the basis of the seven lower-level neighbourhood attributes in Figure 2.1. If each attribute is defined at two levels this would result in 128 (2^7) possible different combinations of attribute levels. In contrast, for the estimation of 'main effects' only, a sheer eight neighbourhood profiles have to be evaluated by a respondent.

Statistically correct estimation of main attribute effects requires the stimuli to be orthogonal, that is, the values of the attribute levels should be independent from each other (non-correlated). This, however, may lead to unacceptable or unrealistic profiles. If no other subset is available, unacceptable profiles may be discarded. Then the design will not be totally orthogonal and this introduces the problem of multi-collinearity among attributes. For the design of fractional factorial designs guides are available. Also most statistical packages featuring 'Conjoint Analysis' contain program modules for the design of sets of orthogonal stimuli. The profiles in the present experiment are designed using the 'Conjoint Analysis' module featured by SPSS-PC+ version 5.0.1 (Norusis, 1992). Orthogonal fractional factorial designs are generated which enables one to estimate the main effects of the value relevant attributes.

1d. Representation of stimuli. Once the stimulus design has been created a presentation method must be chosen. Several methods may be employed for the presentation of multi-attribute objects: physical objects, pictorial or iconic representations, verbal descriptions, or graphic displays. As stated before, in an ideal experimental situation respondents would evaluate actual objects that vary systematically on the relevant attributes. However, for some objects a physical presentation is impractical or impossible.

It would be preferable to construct a set of stimuli that matches real objects as close as possible: actual neighbourhoods would be preferred to video presentations, video presentations to photographs, photographs to iconic representations, iconic presentations to written profiles, and written profiles to graphic (bar) diagrams (Eyles, 1990). This preference order was the result of studies investigating the scenic beauty of landscapes. Correlation coefficients of .80 and higher were found between photo-based evaluations and real landscape evaluations (Daniel and Vining, 1990). Hull and Stewart (1992) corroborated these findings in their study on the relationship between photo-based evaluations and actual landscape evaluations. Their conclusions, however, indicated that these results must be handled with care. Their criticism was related to the fact that all the correlation coefficients were computed on aggregated data. In their study they found no significant correlations between photo-based and actual landscape evaluations at an individual level for 38% of their respondents. Furthermore, video, photo, and iconic representations focus strongly on visual cues of the objects, thereby possibly omitting meaningful psycho-social, tactile, acoustic and/or olfactory cues. Given these considerations it was decided to use verbal descriptions in the present 'CA' experiment.

1e. Number of attributes. When large numbers of attributes have to be considered, as in this study, the number of profiles to be judged by respondents may become too large. Consequently, the judgement task may become too strenuous. If a large number of attributes is unavoidable, several alternative methods are available to deal with this problem. These alternatives are: the 'bridging-type' method, the 'self-explication' method, the 'hybrid' method, and the 'hierarchical information integration (HII)' method (Vriens and Wittink, 1990; Louviere, 1984).

In the 'bridging-type' method the attributes are divided over several subsets of profiles; every subset contains a part of the total number of attributes. For each subset, a separate set of profiles is constructed and a separate judgement task is conducted. The bridge between the subsets is formed by at least one attribute that is shared by all of the subsets. The second alternative is the 'self-explication' method. In this method, the respondent is asked first to evaluate the levels of each attribute on a certain scale. The most preferable level receives the highest score, the least preferable level receives the lowest score. The remaining levels are rated in between. Then, the respondents are asked to assign weights to the attributes, for instance, by means of an allocation method. In this way part-worths, that is, subjective values for each attribute level, can be estimated by multiplying the weight score with the assigned level score. Actually, this is a constructive modelling approach. In this method respondents do not evaluate profiles. The 'hybrid' method combines the 'self-explication' method with the 'full-profile' method. First, part-worth values are estimated according to the 'self-explication' method at an individual level. Subsequently, respondents evaluate a limited set of profiles according to the so-called 'full-profile' method. In the 'full-profile' method objects are represented using all value-relevant attributes (see below). Subsets are drawn from a master set in such a way that all profiles are evaluated at sub-group level of the research population. Finally, in the 'hierarchical information integration (HII)' method (Louviere, 1984) attributes are classified 'a priori' into groups called factors. The term 'factor' here has the same meaning as 'higher-level attribute'. For each factor a set of profiles is constructed on the basis of the attributes belonging to that group. Similarly, for all the lower-level attributes within the factors a set of profiles may be constructed. For instance, a set of neighbourhood profiles may be constructed using the seven lower-level neighbourhood attributes. In turn, the neighbourhood attribute noise may be represented by a set of profiles using its lower-level noise attributes: the specific noise sources.

The attributes in the value-tree obtained in the 'MAU' approach (see above) are structured hierarchically. Therefore, the nested approach of the HII-method makes this approach the most feasible method to evaluate environmental quality attributes holistically. It enables one to assess the relative importance of a relatively large number of attributes while the judgement tasks remain relatively simple. The use of the HII-method will result in various sets of 'residential profiles', that is, profiles are constructed representing dwellings, neighbourhoods, and their respective lower-level attributes (see Chapter 7).

Ad 2. Data collection.

Before data actually can be collected a presentation method and an evaluation method for a set of profiles must be chosen.

2a. The presentation of stimuli. Two frequently used presentation methods in 'CA' are the 'trade-off method' and the 'full-profile method'. The general distinction between the two methods is the number of attributes used in the evaluation of the objects.

Usually, in conjoint analysis a variant of the 'trade-off method' is used. In this form respondents are asked to evaluate pair-wise combinations of attributes. Two attributes are specified by their respective levels. Respondents then are presented with a matrix of these attribute levels: the levels of one attribute vertically, the levels of the other horizontally. Of each possible pair of levels the respondents indicate in what order they are preferred. The advantage of this method is that it can deal with a large number of attributes. However, the pairwise representation of attributes of an object brings along a loss of reality in the presentation of an object. Furthermore, respondents need to keep in mind that with the comparison of each pair of attributes all the other attributes remain constant. Also, 'the trade-off method' is not suitable for an analysis of preferences for objects represented by other means than written descriptions. Finally, the method requires a large number of comparisons to be made, even with small numbers of attributes and attribute levels.

In the 'full-profile method' respondents evaluate object profiles in which all value-relevant attributes are used to represent the object. So if a T.V. set has five value-relevant attributes, these five attributes are used to describe a specific T.V.-set. In contrast to the 'trade-off' method', fractional factorial designs may be employed. Fewer but more complex judgements have to be made. The 'full-profile' method allows for more realistic representations of objects than the 'trade-off' method. The most important drawback of the 'full-profile method' is the risk of information overload on behalf of the respondent. This risk increases if the number of attributes becomes larger. In addition, the order in which the attributes are arranged on the profile card may have an effect on the judgements made by respondents (Vriens and Wittink, 1990).

If the number of attributes does not exceed the total of six, the 'full-profile' method is recommended (Vriens and Wittink, 1990). Because the 'HII'-method is used, the number of attributes for representing objects will be approximately six or less. Therefore the more realistic 'full-profile' method will be used in presenting the profiles.

2b. Preference measure. Profiles may be evaluated by ranking or rating them according to their attractiveness or preference. The procedure is identical to the one discussed in section 3.2.3. In the present 'CA'-experiment (see Chapter 7) sets of profiles are rank-ordered. Additional 'rating' of the profiles would prolong the judgement tasks and would be too time-consuming. In a face-to-face interview the respondent is presented with several sets of residential profiles. Each set of profiles is rank-ordered according to the respondents preference. In contrast to the 'HMR' approach, in which real objects were evaluated, and the MAU- approach, in which no specific residential environments were evaluated, respondents now evaluate experimentally designed representations of residential environments. The respondent rank-orders the profiles in each set from most preferred to least preferred. These rankings may be seen as 'holistic' or 'overall' evaluations. They will be used for the estimation of the relative weights of the residential attributes.

Step 3. Assessment of attribute weights. Attribute weights are estimated by regressing the overall evaluations (rankings) of each profile on its pre-specified attribute levels (for regression analysis see 'HMR' approach). On the basis of these regression analyses 'subjective values' (utilities) are estimated for each level in each attribute. These utilities are used to compute the relative weights of the attributes.

In Summary: In study 4 (Chapter 7) a Conjoint Analysis approach is used, which is a reconstructive modelling approach. In the 'CA' experiment reported, each respondent evaluates various sets of 'residential profiles' (profiles of dwellings, neighbourhoods, and profiles of their respective lower-level attributes) according to preference. The profiles are experimentally designed using an orthogonal array of attributes, all defined at two levels. Profiles are represented on written cards, using all relevant attributes. Each respondent provides only overall evaluations (rankings of the profiles). In the analyses, the rankings are regressed on the prespecified attribute levels. This will result in relative attribute weights estimated for each respondent.

3.4 Comparison of research methods

In the previous section three research approaches have been discussed: the Hierarchical Multiple Regression (HMR) approach, the Multi-Attribute Utility (MAU) approach, and Conjoint Analysis (CA) approach. For each of these three approaches different methods and techniques were introduced to identify attributes and their structure, to evaluate objects, and to assess the relative importance of attributes. In this section the three approaches (HMR, MAU, and CA) are discussed in relationship to each other. For the purpose of the discussion the main aspects of the three approaches have been summarized in Table 3.2.

A first distinction that must be pointed out is the way attributes are inventoried. Two methods are employed: screening relevant literature (employed in the 'HMR' approach) and direct questioning followed by importance selection (in the 'MAU' approach). Attribute selection in the 'CA' experiment is based on the results of the second study (MAU approach). In the 'HMR' approach and the 'CA' experiment attribute selection is done by the researcher. In the 'MAU' approach, direct questioning reveals relevant attributes from the residents. The results of the direct questioning method ('MAU' approach) are used as a check on the completeness of the results of the literature review ('HMR' approach).

Second, two distinct methods to structure attributes will be employed: the 'top-down' approach ('HMR') and the 'bottom-up' approach ('MAU'). Consensus on which approach is best is lacking. More important is that both approaches are used to design a model of environmental quality. The 'top-down' approach, employed be the researcher yielded the theoretical model depicted in Figure 2.1 (see Chapter 2). The results of the 'bottom-up' approach, as employed by the residents, is used to develop a so-called empirical model of 'environmental quality'. The 'bottom-up' approach is a typical method for structuring attributes in a 'MAU' analysis, especially in the 'SMART' (see section 3.3.2). Furthermore it is usually done by the 'decision analyst', in the present case: the resident. As noted before structuring of attributes in a 'HMR' analysis or 'CA' is confined to the researcher. Structuring in these cases may be done by using either the 'top-down' approach or the 'bottom-up' approach or even both.

Table 3.2 Overview of the methods and techniques used in the three empirical studies with reference to the first three steps of a decision analysis procedure. HMR: Hierarchical Multiple Regression; MAU: Multi-Attribute Utility; CA: Conjoint Analysis.

Decision analysis procedure: Approach:	step 1: identify and structure attributes	step 2: evaluate objects	step 3: estimate weights
Study 1 HMR: questionnaire study	- literature - top-down - researcher	- category estimation, - real objects (one for each respondent)	- reconstructive modelling - on group level data
Study 2 + 3 MAU: interviews	- direct questioning - bottom-up - respondents: study 2: residents study 3: 'experts'	- not conducted	- constructive modelling, directly - on individual data
Study 4 CA: experiment	- on the basis of previous findings (study 2) - researcher	- rankings - experimental objects (more than one for each respondent)	- reconstructive modelling - on individual data

A third important distinction that can be made refers to the type of evaluations that are being made (overall evaluations versus single-attribute evaluations). In the 'HMR' approach both types of evaluations are made, and both are made by the resident.

Respondents provide overall evaluations on the higher-level attributes and single-attribute evaluations of the lower-level attributes. In the 'MAU' approach as adopted here, no evaluations of specific dwellings and neighbourhoods were asked. In general in a 'MAU' analysis objects are only evaluated on the end-level attributes. Overall evaluations of an object are calculated by combining the object score on a particular attribute and its attribute weight (single-attribute subjective value) and subsequent aggregation of the single-attribute subjective values. Finally in the 'CA' approach respondents provide only overall evaluations on each of the objects (profiles). Single-attribute scores of the objects are pre-specified by the researcher.

A fourth distinction is the type and number of objects that are evaluated. In the 'HMR' approach each respondent evaluated one real object: his or her present residential situation. The influence of the researcher on prevailing possible objects scores is minimal. As was noted before, this may have an effect on attribute weight estimation: the range of possible object values on a particular attribute influences the attribute weight. In contrast, in the 'CA' approach respondents evaluated several experimental objects. Here, objects scores on the attributes were determined in advance by the researcher. Scores were chosen in such a way that they may reflect the full range of possible scores.

A fifth distinction is the level of relative attribute weight assessment. In the 'HMR' approach, because all respondents only provide evaluations on one object only, relative weights are assessed on group-level data. In the 'CA' experiment, residents are presented with several, experimental objects. In this way, weights can be assessed on an individual basis. This is also the case in the 'MAU' approach: each respondent assigns his or her own weights to the residential attributes

Finally, a distinction can be made between the type of modelling. In two approaches ('HMR' and 'CA') a reconstructive modelling approach is used. Relative weights are estimated on the basis of the co-variance between overall evaluations provided by residents ('HMR' and 'CA' approach) and single-attribute evaluations ('HMR': residents, 'CA': pre-specified by the researcher). In constructive modelling ('MAU' approach) relative attribute weights are assessed irrespective of the object under consideration.

3.5 Concluding remarks

In the previous section differences and similarities among the three empirical research approaches used in this monograph have been discussed. In this section some of the advantages and disadvantages of each method are emphasized.

One of the major benefits of the 'HMR' approach is the high degree of reality of the judgement task. Respondents evaluate real objects. In the present case this is their own residential situation. The internal validity of the results of the study will benefit from this. In contrast, a major drawback of the 'CA' approach may be the representation on written cards of a complex situation such as the residential environment. The degree of reality of the 'CA' judgment task is lower compared to the one in the 'HMR' approach. Consequently it may affect the internal validity of the results negatively.

A further benefit of the 'HMR' approach is that the judgment task can be performed by means of a written questionnaire. In case of a written questionnaire the judgement task is usually easy to perform and not very time-consuming. Furthermore a large number of people may be questioned, which may be beneficial to the reliability of the results of the study. The judgment tasks in both the 'MAU' approach and the 'CA' approach are less simple and also are more time-consuming. The tasks necessary may be best performed in a face-to-face interview. Therefore the number of respondents will usually be smaller.

One of the major drawbacks typical to a 'HMR' analysis is the possible multi-collinearity between attributes (see section 3.3.1). The problem associated with collinearity has been explained already. Here, the advantage of experimentally designed stimuli in the 'CA' approach becomes evident. Attribute levels are combined irrespective of the levels of the other attributes used in a profile. In the 'MAU' approach attribute weights are assessed directly and irrespective of the present residential situation. So, attribute weights are assessed on the basis of their own merit for residential environments in general.

Another set-back of the 'HMR' approach, and usually also of the 'MAU' approach lays in the possible values of the objects on the attributes. These cannot be manipulated by the researcher. This may become a problem when attribute weights are assessed at group level which is the case in the 'HMR' approach. In the 'HMR' approach respondents only evaluate one object. When different environments are evaluated or the same environment is evaluated by different people, ranges of the object value on a particular attribute may fluctuate. Consequently the attribute weight may fluctuate. However, in the statistical analysis employed in the 'HMR' approach these fluctuations are levelled out. In contrast, in the 'MAU' approach and the 'CA' attribute weights are assessed on an individual level thereby accounting for possible variation in attribute weight assignment. In the 'MAU' approach this is established by rating the attributes directly. In the 'CA' approach this is done by judging several experimentally designed profiles of residential environments and each respondent will be presented with the same set of profiles.

In conclusion it can be said that none of the three approaches presented above is best or worst on all aspects. The strengths of one approach are the weaknesses of another. Therefore all three research approaches are employed: they are similar in some respect, different in others. To the extent that the results of the three empirical research approaches lead to the same conclusions, the multi-attribute evaluation of the 'perceived quality of the urban residential environment' presented in this monograph may be considered valid and robust.